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Determination of dew point pressure in gas condensate reservoirs based on a hybrid neural genetic algorithm

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ABSTRACT

Knowing dew point pressure considers as one of the preliminary requirements in retrograde gas condensate reservoir simulations. When the pressure declines below the dew point pressure, the condensate dropouts form, which could lead to a substantial decrease in gas relative permeability and well deliverability. Different methods such as equation of states, empirical correlations and experimental procedures have been proposed to determine the dew point pressure. However, due to their convergence problem, being expensive and time consuming, great efforts have been taken to develop an alternative method. In this study, a new method based on artificial neural network has been developed and optimized by genetic algorithm as an evolutionary technique. A data set consists of 308 sample collected from different sources and literature including one of Iranian gas-condensate field is used. Reservoir temperature, mole percentage of gas components and heavy fractions properties were considered as input parameters to this model. The performance of the proposed model was compared with some of the common correlations and Peng–Robinson equation of state. The results confirmed the accuracy and capability of this model in determination of dew point pressure based on 2.46%, 3.66%, 95.91%, 0.02% and 24.39% as average absolute deviation, root mean square error, correlation of determination, minimum and maximum percentage error; respectively. The sensitivity analysis is also performed on variables to determine the impact and importance of each parameter on prediction of dew point pressure. The results show that plus fraction properties and C_3–C_4 fraction have the greatest positive and negative impacts on estimation of dew point pressure; respectively.

1. Introduction

Gas condensate reservoirs are recognized as valuable, clean and safe source of energy with comparison to other fossil fuels. Therefore, one of the concerns in petroleum industry is finding the most efficient way to produce this kind of energy source [1,2]. Design of processing and transportation facilities of gas condensates and performance optimization relies on a good understanding and knowledge of phase diagram of the system [3–5]. Since the dew point pressure (DPP) is one of the key parameters in retrograde phase diagram, accurate evaluation of this parameter is crucial in order to have accurate calculations in gas reservoir performance and fluid characterization [3,6,7].

At initial reservoir conditions a gas condensate system exists as a single phase fluid and contains short chain hydrocarbons with heavy ends. However, due to presence of less heavy hydrocarbons in condensate gas compared to crude oil systems, it has a smaller phase diagram than that of oil. The critical point is also located at down left side of the phase envelope. Temperature in gas condensate reservoirs lies between critical temperature and cricondentherm. When reservoir pressure declines below the dew line, it leads to separate this fluid into two phases, a gas phase and a liquid phase, which is known as retrograde condensate [6–8]. Forming the condensate phase and its accumulation nearby the wellbore plays an important role on reduction of well deliverability. Some authors reported the severity of this decline by a factor of two to four [9–17]. On the other hand, understanding the causes of the production decline of a gas condensate well would be helpful to decide right action to run. For instance, gas production decline might be due to either mechanical formation damage or condensate blockage that each one requires their own approaches to tackle with [6]. Thus, estimation of dew point pressure is crucial to better evaluate reservoir conditions.

Different methods such as experimental methods, equation of states (EOS), empirical correlations and recently artificial

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Nomenclatures

Acronyms

AAD	Average absolute deviation
ANN	Artificial neural network
BP	Back propagation
CCE	Constant composition expansion
CVD	Constant volume depletion
DPP	Dew point pressure
EOS	Equation of state
GA	Genetic algorithm
LM	Levenberg–Marquardt
MSE	Mean square error
PR-EOS	Peng–Robinson equation of state
RMSE	Root mean square error
SPSS	Statistical Package for the Social Sciences

Variables

F	Fahrenheit
MW	Molecular weight
N	Number of samples
P	Absolute pressure
P_d	Dew point pressure
R^2	Correlation of determination
R	Universal gas constant
Sp.Gr	Specific gravity
T	Absolute temperature
V	Volume
f	Fugacity
k	Equilibrium ratio
k_{ij}	Binary coefficient
x_i	Composition of the liquid phase
y_i	Composition of the vapor phase
z_i	Overall composition

Greek letters

α	Dimensionless factor
γ	Specific gravity
φ	Fugacity coefficient
ω	Acentric factor

Subscripts

i	ith composition
j	jth composition
e	Experimental value
p	Predicted value

intelligence with their own benefits and drawbacks have been employed to estimate the dew point pressure [7]. Generally constant composition expansion (CCE) and constant volume depletion (CVD) tests are used in order to estimate the dew point pressure [2,6]. However, CVD test is performed for gas condensate and volatile oil because these fluids experience a considerable compositional change when the pressure dropped below the saturation pressure. Moreover, CVD test is performed in such a manner as to simulate depletion of the actual reservoir by assuming immobility of dropped out condensate in porous media therefore the results of this test is more similar to the gas condensate reservoir conditions [18]. In this test, the volume of a high pressure PVT cell is kept constant as a result of expelling the excess gas at each pressure depletion level, one can determine the dew point pressure as well as thermodynamic equilibrium and change of fluid composition [4,19]. Despite the accuracy and reliability of experimental methods in determining PVT properties such as dew point pressure, these approaches suffer also from high cost and being time consuming. In addition, the difficulty in obtaining of appropriate samples and subjection of experimental measurements into many errors are fundamental drawbacks of using such methods [6,7,16,17,20]. Using EOS, as a most common thermodynamic method, is another way to determine the dew point pressure. Generally EOSs are developed for pure components, therefore applying those to multi components such as petroleum fluids bring some inaccuracy. This point highlights the impact of proper characterization of plus fractions as the main source of uncertainty in EOSs predictions of reservoir fluid behavior. Calibration of EOSs to experimental data, to some extent, helps to tackle with these uncertainties in fluid properties. However, due to convergence problem near the critical point, prediction of thermodynamic properties of reservoir fluid considered as a major limitation of using EOSs [2,7,15–18,20–27]. Other predictive methods to determine dew point pressure are empirical correlations. They are relatively easy to use, however, they are not accurate at high temperature and pressure conditions. Different parameters used in these correlations include temperature, hydrocarbon composition and plus fraction properties. Recently, different empirical correlations were developed to determine dew point pressure by various authors [7,15–17,20,28,29]. In recent years, usage of artificial intelligence techniques specifically neural network with their unique ability to derive relation from complex data has been increased. Due to complicated nature of retrograde condensation and capability of artificial neural networks (ANN) on solving non-linear and non-parametric problems such as dew point pressure determination, these massive parallel processing techniques play an important role in petroleum engineering [16,17,20,21,30–32].

Various researchers have been tried to better estimate DPP by employing ANN and evolutionary techniques. Improved neural network base model of González et al. and neural fuzzy system of Nowroozi et al. are among the most well-known investigations in this regards. Rostami and Manshad also studied the impact of evolutionary techniques on accuracy of DPP data, which were extracted from ANN model in which Gaussian process regression and particle swarm optimization were used [7,2,33].

In this study, a new intelligence method in purpose to predict dew point pressure as a function of temperature, gas composition and plus fraction properties is used. To get better results, the model was optimized by genetic algorithm (GA) as an evolutionary technique. The model performance was evaluated by comparing the results with the performance of Peng–Robinson equation of state (PR-EOS) (see Appendix A) and some general correlations for dew point pressure prediction such as Nemeth–Kennedy and Elsharkawy [15,28,34] (see Appendix B). The results that will be discussed in next sections proves the robustness and the accuracy of the proposed GA–ANN model.

2. Artificial neural networks

Artificial neural networks are powerful systems, which are inspired by the biological nervous system and aimed to simulate the learning process in the human brain. The ANNs have a history of more than 70 years, however their applications have been developed and matured in the past two decades [35–43]. ANNs are composed of interconnected artificial neurons and characterized by their architecture (e.g., the numbers of layers), network topology (feed-forward or recurrent) and learning algorithm (supervised or unsupervised) [44]. They include an input layer, one or more hidden layers and an output layer [45–47]. Each layer